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Assessing the AI Adoption. The Global AI Index Dataset Used to Build, Train and Test a Machine-learning Algorithm.

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Abstract: The paper aims to analyse the AI adoption at the company/country level and the efforts made to achieve this objective. The necessary changes for the use of AI solutions involve not only a significant financial effort, but also attracting talent, building adequate infrastructure, getting governmental support and, above all, consistent investments in research and development at the company/country level. The paper presents the key elements of the measurement process used in calculating the Global AI Index, as well as the results for 62 countries, having as an original contribution the creation, training and testing of a machine learning algorithm, aiming to extrapolate the AI Global Index. Also, the purpose of the paper is to demonstrate that AI machine-learning models can be created, trained and tested to achieve a higher accuracy of forecasting and can be used regularly in the decision-making process. The scientific journey was possible due to open access to the data used to determine the AI Global Index, as well as to the use of collective experience and wisdom (e.g. Google Colab and Python programming language). Even though the results have just a demonstrative value encourages the research expansion to calculate the Global AI Index for Romania, a country which is not listed among the 62 countries for which the Global AI Index was calculated in 2023.

Keywords: artificial intelligence, Global AI Index, machine learning, algorithm,

Introduction

Nowadays, new technologies emerged and looking for higher economic performances, companies are eager to innovate incorporating state-of-the-art IT solutions to increase their competitiveness in the global economy. In the last decade, the top management faced a lot of challenges related to the adoption of new disruptive technologies and their reaction was complex in diversity. Referring to AI solutions able to improve companies' performance, professionals' and practitioners' voices are quite divergent. Some are considered highly innovators and are eager to use AI solutions in supporting the decision-making process, others milde innovators focus on adopting AI solutions in task automation, and conservatives, being the majority, still waiting for confirmation of the AI. Apart from these categories, the critics are vocal in considering AI just a bluff, a fashionable topic in discussions but still AI not confirm the majority's expectations.

Looking at AI adoption in companies, across the world, it must be seen as a two-way process: AI solutions adopted to support decision-making and to ensure task automation with a significant impact on operating costs reduction. In the last years, for example, the "cost of predictions started to downsize at an accelerating pace" (Agrawal et al. 2022) and

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the interest grew in "where AI will be incorporated" and "what its impact on business and employment" will be (Gans and Leigh, 2019). If one analyses the recent developments in AI will conclude that most of them are related to the advancement in machine learning, especially allowing low-cost prediction (e.g. forecasts or nowcasts of a variable using existing data, with non-additional costs.

For economic reasons mainly, nowadays decision-makers choose between humans and machines and almost every single time it is selected the least expensive of both. Different industries registered AI adoption based on their understanding and their experiences, but economic efficiency dominates. The competition race forces companies to innovate (at the products or services level), to eliminate unnecessary or to reduce costs to maintain their competitive advantage. So, AI adoption requires changes in the company's organizational structure if we talk about AI-assisted decisions, which involve coordination between modules. Some organizations are not in favour of such major changes at the decisional and coordination levels and prefer task automation and cost reduction. Overall, AI as a new emerging technology has been embedded differently depending on the company size, industry or country.

The total number of English-language publications (journal articles only) worldwide nearly tripled from 2010 to 2022, a total of 88,000 in 2010 to more than 240, 000[1]. The machine learning field generated the highest proportion of them (around 31%). But papers presenting major innovations are few, and those generating machine learning models do not come from academia, they come from industry and industry-academia cooperation mainly because of the costs of computational resources required to train and operate a machine learning model. Young talent advancing knowledge in the field decided to act collaboratively establishing communities of programmers, exchanging apps, and code lines, and talking about how to progress and the phenomenon is growing rapidly.

The paper aims to analyse AI adoption at the country level, taking into consideration all the above-mentioned individualities existing at the company level and across industries. What is important to emphasise is the fact that AI will revolutionize not only the business world but also society and government. A recent enterprise survey reveals that the use of AI for analytical purposes is driven by cost reduction in current operations and immediate revenue increase, especially in marketing and sales. "Across most industries, the survey results suggest that organizations are finding off-the-shelf offerings applicable to their business needs—though many are pursuing opportunities to customize models or even develop their own" (McKinsey, 2024). The starting point was the Global AI Index[2], developed by Tortoise Media as being "*the first index to benchmark nations on their level of investment, innovation and implementation of artificial intelligence*." The 2023 Global AI Index is the fourth iteration and it is calculated for 62 countries, unfortunately, Romania is not among them, but the newly released 2024 GAII includes 83 countries, among which is Romania this time, ranking 50.

The paper benefits from an extensive literature review, and a deep insight into the Global AI Index methodology, and allows identification of the main characteristics of such statistical endeavour of using machine-learning capabilities and Phyton programming language to create a machine-learning algorithm, and after training and testing it. Even though the dataset is limited in volume, the paper's scientific value resides in demonstrating what a machine learning algorithm, even the simplest one, can do to support business decisions and research as well.

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[1] https://aiindex.stanford.edu

[2] https://www.tortoisemedia.com/intelligence/global-ai/

Literature review

The current research started with a systematic literature review which consisted of a selection of articles based on relevance, year of publication, authors' affiliation looking for concepts' explanations, theory developments, methodological approaches and tools to be used in the demonstration.
A table summarizing the literature review results is provided to help readers choose where to go in deep upon their particular interest.

Artificial Intelligence & Machine Learning

The interest of researchers and also business people has grown constantly in the last decade on artificial intelligence and how it can be employed helping companies to increase their profits and maintain competitive advantage in a business world dominated by fierce competitors. Researchers agree that artificial intelligence is an emerging technology serving the general purpose (Cockburn et al., 2019) that will revolutionise how companies will perform their activities. But adoption of new technologies is never easy, maybe because humans are programmed to be resistant to change, to delay or to question in many possible ways what they can't understand or what they cannot accept as possible. When it comes to the business world, is even harder - companies are structured organizations that perform various tasks daily and the decision-making is a process carefully managed and introducing change is more challenging when it comes to AI. From simple automation of tasks, and tools able to enhance forecasting accuracy to more complicated solutions from the area of generative AI, the new technology supports a high level of innovation if adopted in all range of company's activities. The adoption of AI and machine learning in business intelligence brought a lot of challenges and opportunities (Bharadyia, 2023).

AI is widely accepted as the newest general-purpose technology (GPT) (Goldfarb, Taska, & Teodoridis, 2020; Tratjenberg, 2019), following other major technological innovations such as information technology (IT), computers, and do not forget electricity. According to the European Commission's Communication on AI, (ECC, 2018) "Artificial intelligence refers to systems that display intelligent behaviour by analysing their environment and taking actions – with some degree of autonomy – to achieve specific goals". Going deeper, what is called today "generative AI" means systems that provide sophisticated, high-performance tools even though they are not yet equipped with "creative" human-like minds they start to play an increasingly important role in the corporate innovation process. The machines' ability to process and analyse large amounts of data creates a higher level of knowledge and therefore AI becomes a valuable tool in the decision-making process supporting managers (as decision-makers) to navigate in a more and more complex and complicated business environment.

The AI benefits are promoted across industries or fields of science, and no doubt these benefits exist and are measured through financial performance, innovation outputs and just to name a few of them. Although critics' voices are lauder and lauder, some critics say that artificial intelligence is just a "fashionable" word, a construction used mainly for marketing purposes. Going deeper, the critics ask heavy questions, and the first difficult one is Can we trust AI? (Bedue & Fritzche, 2022)

Machine learning as a subset of AI enhances and expands business intelligence capabilities. It helps companies get valuable insights from the huge amount of data they collect, automate repetitive tasks, improve processes and forecast more accurately to make better decisions (Kilanko,2023). Machine learning means studying algorithms and statistical models that computers are using to perform specific tasks without being explicitly programmed. It involves various algorithms that are used in applications such as data mining, predictive analytics, forecasting, and image processing. While artificial intelligence (AI) is "large and abstract" and has to do with making computers "think" and "act" similarly to human beings, machine learning algorithms, as a subset of AI, are

designed to automatically learn from data without being explicitly programmed (Moroney, 2020). ML is employed to teach computers to handle large data more efficiently. Just looking at data, one cannot interpret the information extracted from this dataset, therefore an ML is needed and the global demand is rising fast, mainly because many industries apply ML to extract relevant information from data.

Today, ML is the most rapidly growing area of study, located at the crossroads of computer science and statistics and situated at the core of artificial intelligence and data science (Jordan & Mitchell, 2015). It is widely recognised the fact that machine learning together with deep learning are the most revolutionary areas of AI. The popularity of both increased mostly because of their ability to analyze large datasets and provide valuable insights which previously were difficult to obtain and required high costs. Since 2010 the progress in the machine learning field improved the computers' ability to make predictions from historical data. In fact, "the maturity of an ML modelling technique called "neural networks", along with large datasets and computing power, have been behind the expansion in AI development and its adoption" (OECD, 2019)

In this paper the focus will be kept on Machine Learning, leaving deep learning for further endeavours. Machine learning methods are diverse and users take advantage of all of them depending on what they want to achieve and with what resources. Figure 1 illustrates the diversity of methods, each of them being developed to solve a certain kind of problem.

Briefly, the following types of machine learning are currently employed:[3]

- *supervised learning*: used to solve two kinds of business problems regression and classification, e.g. customers' segmentation in classes of preferences;
- *unsupervised learning*: usually for unlabeled data and having as its main purpose to reveal patterns and relationships within the data ;
- *reinforcement learning* means using an agent to interact with a specific environment and learn how to act to maximize rewards over time.

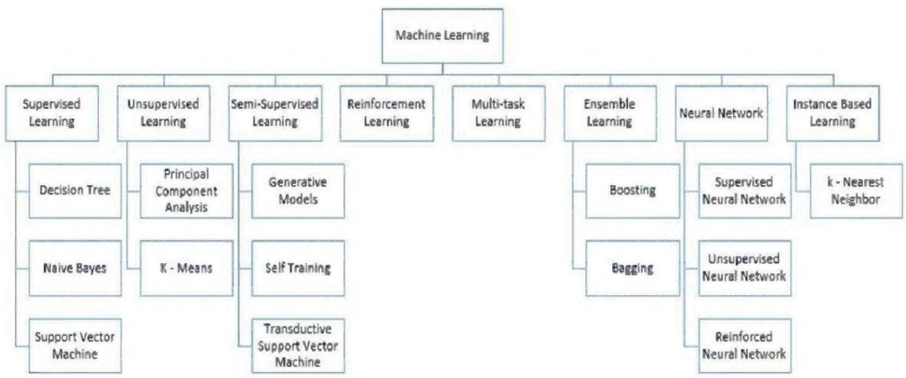


Fig. 1 Machine learning – a classification of the most common methods
(Source: Mahesh, 2020)

AI adoption worldwide – experiences and results/costs

Adoption of new technologies has always been difficult, and the resistance to change at individual and corporative levels is to blame no matter countries or cultures. New and disruptive technologies, such as AI and machine learning, require organizational change (Uren & Edwards, 2023) to better adapt the organizational functions powered by AI. Human factor always plays a crucial role because resistance to change comes from

[3]https://manish-gupta.medium.com/machine-learning-and-commonly-used-algorithms-a-comprehensive-overview-debe88321909

misunderstanding, fear for their jobs, lack of skills for AI, misperception of consequences or not seeing the AI benefits which appear a long time after the first AI implementation. However, AI is "human-enhancing innovations" and not "human-replacing innovations" (Trajtenberg, 2019)

The performance, usually related to high-tech companies, varies from one company to another mainly because the AI adoption intensity is quite different. The company revenues increase only if there exist significant investments in AI solutions and hardware, and the benefits are far greater for companies which invest in complementary tech solutions and implement an internal R&D strategy. The investments made in complementary technologies alongside organizational change make it possible to accommodate AI-related activities (Felten et al., 2019*)*. Suk Lee et al. find that such "performance gains from AI adoption are larger among firms that invest in complementary technologies such as cloud computing and database systems". Moreover, the positive relationship between AI adoption intensity and revenue growth is stronger among firms that pursue a more exclusive R&D strategy specific to the venture" (Suk Lee et al.2022). Suk Lee et al. 2022 views are consistent with the results of Calvino & Fontanella 2023 in demonstrating that the firm's digital infrastructure (ultra-fast broadband, cloud computing etc) is playing a major role in AI adoption, and a positive one as is illustrated in the regressions computed.

In conclusion, there are relevant studies suggesting that firms need to heavily invest in complementary technologies to better support AI adoption and to enjoy AI adoption benefits as well. Also, the firm digital infrastructure and the use of cloud computing play a significant role in all AI solutions implementation. Moreover, the intensity of adoption is also dependent on these expensive assets.

Also, Calvino & Fontanella conclude :

- higher shares of AI users appear across younger firms;
- shares of AI adoption are consistently higher in ICT and professional services (that suggests that AI adoption is different from one industry sector to another);
- AI users are more productive than others, but the increase in productivity is not only because of AI.
- Skills and innovation are factors linked to AI adoption as well.(Calvino & Fontanelli, 2023).

Measuring the impact of AI adoption became desirable and indicators were developed, for example, to link the level of investment in operational systems and the AI adoption benefits, such as the revenue boost. McKinsey Company ran a survey on this matter and the results show more than 65% of respondents report that their organizations use generative AI, almost double the percentage from those included in the previous McKinsey AI Adoption Survey, which ran just ten months ago (McKinsey, 2024). The future looks promising in the area of investments, 67 % of the interviewed companies expect their organizations to invest more in AI over the next three years.

Moreover, AI adoption is shaped by a series of factors which can be common to all or quite different depending on the industry sector or country where adopters are situated. Studies have some highly significant factors such as AI ethics, perceived benefits, clarity of the AI role, perceived trust and also the gained competitive advantage (Polysetty et al.,2023). An OECD study establishes "the link between AI use, firm characteristics, and factors complementary to AI use. It provides for the first time an international outlook on AI adoption based on firm-level data analysed in a harmonised way" (Calvino& Fontanelli, 2023). It seems that large firms have twice as a share of AI users and that could suggest

the existence of a scale advantage possibly due to high costs in AI adoption but the findings are in line with the existing specific literature (Alekseeva et al. 2021, Babina et al. 2020).

Measuring the AI adoption

Things get complicated when it comes to assessing, as accurately as possible, the level of AI adoption. Some measurements focus on investments related to AI incorporation, in terms of costs for hardware, and cloud services but also the costs of high-skilled employees working with the new technology. Other measurements look at revenue growth which usually is reached in those companies with a high level of AI adoption. For those companies that are just testing the AI solutions or have a low level of adoption, it is not yet possible the isolate and measure how much of the revenue increase is due to AI adoption itself. There is significant literature concluding that the productivity benefits of AI adoption are not so evident in the early stages of adoption but appear in later stages, especially in those companies investing large amounts of money as well as operating necessary changes at the organizational level. *(*Jovanovic & Rousseau, 2005; Bresnahan, 2020; Majumdar et al., 2010).

The literature review shows that there is “ limited comprehension or relevant insights to demonstrate to what extent AI adoption is related to firm performance and what moderators facilitate or act as barriers to achieving success in AI adoption.”(Oduro et.al.2023). Oduro et al. examined how digital technologies, such as AI and big data, are influencing the firm performance and what are the conditions that enhance the results. Their findings are the following: the AI impact on firm performance exists and is significant, and the most relevant performance indicators are: financial performance, innovation and operational efficiency. Moreover, it has been demonstrated that AI applications could increase the market share, generate higher revenue and profits, enhance innovation and improve efficiency.

Rialti et al. (2019) describe the existing research as “still theoretical or at most qualitative,” and that it offers a “limited understanding of the investment return of AI and the strength and direction of the quantitative relationship”. Other research reported inconsistent findings because the adoption of AI takes time and significant effort not only financially but also in changing the mindset.

At the firm level the measurement of AI use is rather rare, in Europe are some pieces of evidence but the samples are small to be relevant (e.g., Czarnitzki et al., 2023; Hoffreumon et al., 2023). There have been published studies on this topic also in Canada and China relying on different approaches (Alexopoulos & Cohen, 2018; Berajaet al., 2023).

Attempts to quantify AI adoption at the firm/country level are increasing in numbers especially in the last 3-4 years, demonstrating the fact that not only large firms are interested in incorporating AI in daily operations but there has also been a growing interest in measuring the AI diffusion at country level.

No doubt, AI is transforming business models and driving transformative change at the company level and the country level as well. The digital transformation involves “the use of new digital technologies to enable major business improvements in operations and markets, such as enhancing customer experience, streamlining operations, or creating new business models” (Paavola et al., 2017, p. 2)

Building ML algorithms

Why an ML algorithm? The usefulness of ML algorithms is beyond any doubt. ML algorithms are used by an AI system to realize tasks, such as to get insights and reveal patterns and also, to predict outputs using a set of inputs. Therefore, algorithms enable

computers to learn (IBM)[4]. What is really important to know is that the algorithms can be trained to learn from data to generate more accurate predictions. So, using statistical methods, these algorithms can uncover key insights which can be used to support the decision-making process.

The process of building algorithms is multistage as follows[5]:

- First, a decision process – ML algorithms use an input dataset, labelled or not, to predict or identify a pattern in the data.
- Second, an error function – is employed to evaluate the prediction of the algorithm. The function makes a comparison of what is known to evaluate the precision of the model.
- Third, a model optimization process – if the algorithm fits better to the data included in the training set, then the weights are adjusted to diminish the differences between the known example and the estimated one. The algorithm will do it repetitively – evaluating and optimizing until the established accuracy is met.

In the case of supervised learning, it has been used a training dataset to help models learn to attain the desired result. So, the input dataset includes also the correct outputs that help the model to learn over time. The algorithm measures its accuracy adjusting until the error is been minimized sufficiently.

The ML algorithms can be used in various business functions, for example, advanced ML algorithms are particularly useful in bringing precision to marketing analysis based on large datasets and help decision-makers to understand a lot of details bout clients and increase firms performance. To conclude, ML algorithms are used to enhance the capabilities of an AI application.

Looking to assess the effectiveness and the efficiency of an ML learning model is needed to analyse the nature and features of data and the performance of the algorithm itself. The most popular ML algorithms perform: regression, classification, data clustering, and association rule learning and more advanced of them are used to develop reinforcement learning. The crucial aspect of building an ML algorithm and a data-driven system is the availability of data, which can be found in different forms or structures. It depends on the programmer to make this data usable.

Methodology

Taking into consideration the variety of methods used to measure AI adoption at the firm/country level, as the current literature review shows, and having as the main purpose of better understanding how the adoption process is taking place, a series of research questions have been formulated as follows:

1. Could AI adoption improve firm performance?
2. What are the factors that influence AI adoption at the country level/company level?
3. What a machine learning algorithm can do to illustrate AI adoption dynamics?

First, a systematic literature review was undertaken to identify, select and critically appraise (Dewey, A. & Drahota, A. 2016) and the main results are organized in a summary table (see Table 1).

The literature search was restricted to the 2020-2024 time frame, mainly because the most relevant technological progress in the AI field occurred in the past recent years. The

[4] https://www.ibm.com/topics/machine-learning-algorithms

[5] https://ischoolonline.berkeley.edu/blog/what-is-machine-learning/

research used Scopus and WoS Clarivate to identify the relevant and highly cited papers discussing AI adoption, machine learning and firm performance driven by disruptive technologies.

The literature review reveals the complexity of this field, the interest is growing from theoretical and practical perspectives as well. A snapshot presented in Table no.1 hopefully will be helpful to any researcher who starts looking at this area of research. The results are grouped in several categories and for each was evaluated the usefulness.

Tabel no.1 A snapshot of the literature review

Authors/year	Concept/theory/method	Explained	usefulness
Artificial Intelligence & Machine Learning			
Cockburn et al., 2019 Trajtenberg, 2019	Artificial intelligence	AI is an emerging technology for general purpose AI is human-enhancing innovation not Human-replacing innovation	Defining the research field
Bharadyia, 2023	Business intelligence	AI & ML adopted in BI generate a lot of changes and opportunities	Connecting AI &ML with organization functions
Goldfarb et al. 2020; Tratjenberg, 2019	General purpose technology (GPT)	AI is the newest technology that creates innovation breakthrough	Explaining why AI is revolutionising the way firms operate and decide
European Commission, 20218	Artificial intelligence	Definition – a system that manifests intelligent behaviour in analysing and taking action - a system with a certain degree of autonomy	Defining the concept
Bedue & Fritzche, 2022	Is AI trustworthy?	Trust issues and criticism – AI is not perfect and doesn't provide universal solutions	Criticism is good to have a wider perspective.
Kilanko, 2023	Machine Learning Business Intelligence	ML =use of algorithms	ML enhances and expands BI capabilities ML get insights from large amounts of data ML helps automation of tasks
Moroney, 2020	AI vs. ML	AI is "large and abstract" and has to do with making computers "think" and "act" similarly to human beings. ML is about teaching computers how to learn	Understanding the difference between concepts and using them correctly.
Jordan & Mitchel,2015	Machine learning positioning	ML is located at the crossroads of computer science and statistics and situated at the core of AI and data science.	A better understanding of the research field of study;

			Helping to make useful and logical connections

OECD, 2019	Neuronal networks Computer power Data	Explain AI adoption and expansion	Understanding the evolution of AI what are the drivers and how goals achieved
Mahesh, 2020	ML classification	Supervised learning Unsupervised learning Reinforcement learning	To be able to use appropriately a method one needs to know what is about
Uren & Edwards, 2023	AI and resistance to change	Adopting new technologies is a challenge and an opportunity as well	Having a perspective from inside organizations on their way to implementing AI
AI adoption worldwide – experiences and results, costs			
Felten et al., 2019 Suk Lee et al., 2022 Calvino &Fontanella, 2023	AI & firm performance AI & revenue growth AI & complemen-tary technologies investment	Performance increases if large amounts are invested in complementary technologies (e.g. cloud service)	Understanding the relationship between AI adoption and firm performance & revenue growth
Measuring the AI adoption			
Gartner, 2017, Alsheibani et al., 2019, Willcocks, 2020, Sjödin et al., 2021	Impact of AI adoption	Measurement Impact factors Benefits	Rise awareness of what are the benefits and how can be evaluated.
McKinsey, 2024	Global AI Adoption Survey	Firms' perception of AI adoption	Statistics reveal the growing interest of firms to invest in AI
Polysetti et al., 2023	Factors influencing the AI adoption	AI ethics, perceived benefits, clarity of the AI role, perceived trust and gained competitive advantage	It seems that adopting AI in firm operations is paying off.
Alekseeva, 2021 Babina, 2020	Analysis of AI Adoption Benefits	Advantage of scale for large-size firms High fixed costs to support	The success of AI adoption depends on the pre-existing assets and operational capacity.
Oduro et.al.2023 Rialti et al. 2019	Measurement approaches	Limited comprehension and less evidence to link AI adoption to firm performance	It exists an interest in developing measurements but the process is in the early stages.

Source: Author's work

The research results have been organized into 3 categories examining the connectivity between AI progress and the impact on firm performance. Geographically, the research included Europe, the USA and Asian countries (China, Japan, and Korea). The empirical

data have been analysed and the authors' findings were classified to be correlated and to identify what is common to all.

The main conclusions are:

- AI adoption requires a strong commitment to investing in complementary technologies that better support the necessary changes in the firm's operations;
- AI adoption is highly dependent on large investments in research and development and ROI will increase therefore one can conclude that AI adoption is paying off;
- AI adoption involves not only changing the mindset, but most of all, creating the conditions inside organizations to accommodate the change, to diminish resistance to change. Sometimes people are reluctant to change especially if is perceived as a danger to their jobs.
- Human capital is a key element that should be considered in AI adoption because a) talented and highly skilled professionals are needed to work in the new AI environment; b) AI impacts people's productivity hence firm performance; c) AI task automation will impact how labour is allocated inside the organization;
- The benefits of AI adoption are highly dependent on implementation, degree of innovation and investments.
- There is an increasing interest in measuring AI adoption, from the firm level to the global scale. McKinsey, Stanford, International Monetary Fund, just to name a few of the powerful academia and business consultants interested in offering tools that might help organizations to navigate through such disruptive change in the daily operating system;

To conclude: Could AI adoption improve firm performance? The answer is yes and it depends on talent acquisition, AI implementation, investments in complementary technologies and infrastructure, and designing a solid R&D strategy. The benefits of AI adoption are directly proportional to the size of the firm, large firms are more likely to earlier collect the benefits.

Based on the literature review it has been identified five AI indexes that are consistent with the above-mentioned findings:

- Global AI index[6] (GAII)- calculated by Tortoise is a composite index which reunites 24 different data sources, from government to public data, from international organizations to specific companies. 122 indicators were weighted and scored to aggregate in a total score for country comparison reasons. For the current paper, the structure of the index is relevant, the data captures three areas of interest: implementation, innovation and investment, and seven sub-areas such as talent, infrastructure, operating system, research and development, commercial ecosystem and government strategy. The GAII was calculated for 62 countries in 2023 and the recently released GAII 2024 has been calculated for 83 countries, Romania being for the first time on the list, ranking 50, with a high score of 56 at talented professionals from a maximum 100, 34 and 32 at infrastructure and operational environment, scoring 56 at research and only 25 at development and quite good at government strategy 65 and commercial ecosystem 62. Ranking 50 from 83 countries, Romania has good perspectives on AI adoption.
- AI Watch Index EU[7] is a measurement developed by the Joint Research Center, focusing on the global AI landscape, industry, research and development, technology and social aspects.

[6] https://www.tortoisemedia.com/intelligence/global-ai/#pillars

[7] https://ai-watch.ec.europa.eu/ai-watch-index-2021_en

- AI Preparedness Index (AIPI) – elaborated by the International Monetary Fund measures the firms' capacity to implement AI in their operations.
- AI Index Report – HAI Stanford University (Human-Centered Artificial Intelligence)
- IBM Global AI Adoption Index[8] – 2023
- AI adoption report – survey-based data highlighting the barriers and .....

The initiatives in setting reliable measurements are numerous and they have in common the attempt to quantify the boost in performance that AI solutions can bring.

Q2 : What are the factors that influence AI adoption at the country level/company level?

Analyzing AI index constructs one can observe the prevalence of factors that are supporting AI adoption at the firm/country level. The most significant factors are:

a) Human capital – AI adoption started in small and innovative firms with the benefit of having young and highly skilled professionals which initiated the automation of daily tasks, usually time-consuming and the immediate result was a boost of efficiency. Attracting AI talents is challenging as well because of the scarcity of this resource and due to the high salaries required. E.g. From 126.000 USD/year for a machine learning engineer to 130.000 USD/year for a computer vision engineer and 160.000 USD/year for a Director of machine learning are not accessible to small firms, and therefore access to such human resources is kind of restrictive.

b) Investments – actually to implement AI means to start by using solutions such as automation of some of the tasks or just one operational field to implement AI integrated platform to deal with decision-making, products/services optimization and a lot more. Investing in complementary technologies (namely just one such cloud service) is not for everyone, the costs are high and in the early stages of AI adoption, the benefits are not obvious and quantifiable.

c) Research and Development – companies should design their internal strategy to engage in productive research and to enhance their capacity to marketize the research results. Big 5 companies that are leading the AI adoption invested billions in research and developments before getting benefits. The innovation wave started, small and medium-sized companies started to innovate one at a time and use AI in marketing and sales as a start, forecasting and predictive analysis etc.

d) Government support - is crucial to create a favourable environment to encourage AI to get implemented and grow in as many companies as possible. Early adopters – usually highly innovative start-ups have been supported by governments through targeted policies.

Despite the enthusiasm of early AI adopters, some barriers arise :

- Can AI be trusted? The trust issue is strongly debated nowadays, for example, managers do not trust enough machine capabilities to adopt strategic decisions no matter how much data is analysed.
- The ethical dimension of AI adoption needs to be discussed.
- Quality assessment of data starting with data collection, data privacy and mitigating the identified biases
- Does AI need to be regulated more strictly to avoid biases and their impact?

[8] https://newsroom.ibm.com/2024-01-10-Data-Suggests-Growth-in-Enterprise-Adoption-of-AI-is-Due-to-Widespread-Deployment-by-Early-Adopters

Being an interesting topic, the measurement of AI adoption generated in the last years a diversity of research, from experimental to theoretical, trying the better understand how companies/countries are progressing in this direction.

Q3: What a machine learning algorithm can do to illustrate AI adoption dynamics?

An ML algorithm can be used to predict, based on the input dataset, what is going to be in the future. How this works is explained below. Was organized an experiment in a supervised environment to test if such an ML algorithm is working and with what results.

Experimental methodology

The Global AI Index (GAII) generated a dataset which can be used for experimental purposes such as building a machine learning algorithm able to work with this specific data.

The research questions mentioned above tackle the factors of AI adoption and a machine learning algorithm incorporating these factors can learn from data, can be trained and tested to use it for predictions.

It has chosen a supervised machine-learning algorithm to be built using the Phyton programming and as the work environment, it has employed the Google Colab platform. Building a machine learning algorithm was a step-by-step procedure as follows:

Step 1. Organizing the work – Having in mind that is an experimental endeavour, it was searched public datasets having the variables used to calculate the Global AI Index. The Kaggle Machine Learning and Data Science community provided access to a wide range of datasets, from which it has extracted the .csv file displaying data used to calculate GAII[9]. The dataset includes the variables used to calculate the GAII index as follows:

- Variables to characterize the implementation phase: Talent, Infrastructure, Operational Environment
- Variables to describe the innovation component: Research, Development
- Variables to describe investment: government strategy and commercial ecosystem.

Table nr. 2 AI adoption pillars

Pillars		*Variables*	Weight (%)
Implementation	30%	Talent	15%
		Operating environment	4%
		Infrastructure	11%
Innovation	40%	Research	22%
		Development	18%
Investment		Governmental Strategy	8%
	30%	Commercial ecosystem	22%

Source: Adapted from Tortoise Media

[9] https://www.kaggle.com/datasets/katerynameleshenko/ai-index

The total score (Y) is calculated using a linear function taking into consideration the contribution of all seven variables, each being weighted according to the impact on AI adoption.
The working environment was established in Google Colab (Gcolab) where a Notebook was created. Using the Python code writing and combining it with the explanatory text helps the researcher to track all previous actions. Figure 3 illustrates how the notebook is organised and how the coding and text windows are displayed.

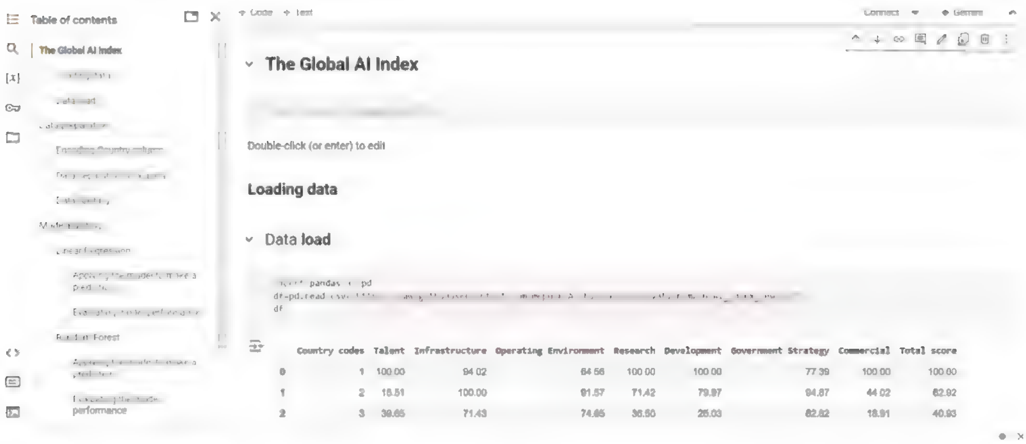
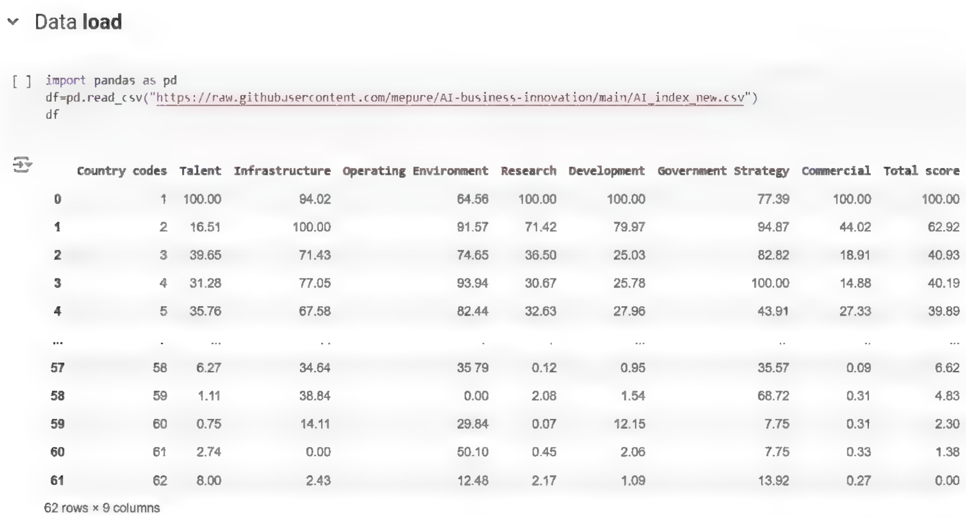


Figure 2 ML Python coding in Google Colab
Source: Author's work

Step 2. Prepare the dataset –have a clear view of the dataset features. To organize the experiment of building a machine-learning algorithm, the first step was to prepare and load data. The Global AI Index file is available in format .csv. It was uploaded on GitHub and then using Python code was imported into Google Colab.

```
import pandas as pd
df=pd.read_csv("https://raw.githubusercontent.com/mepure/AI-business-innovation/main/AI_index_new.csv")
df
```

Once the dataset is imported, the columns and lines are visible in the workspace, see Figure 3



Data load

```
import pandas as pd
df=pd.read_csv("https://raw.githubusercontent.com/mepure/AI-business-innovation/main/AI_index_new.csv")
df
```

	Country codes	Talent	Infrastructure	Operating Environment	Research	Development	Government Strategy	Commercial	Total score
0	1	100.00	94.02	64.56	100.00	100.00	77.39	100.00	100.00
1	2	16.51	100.00	91.57	71.42	79.97	94.87	44.02	62.92
2	3	39.65	71.43	74.65	36.50	25.03	82.82	18.91	40.93
3	4	31.28	77.05	93.94	30.67	25.78	100.00	14.88	40.19
4	5	35.76	67.58	82.44	32.63	27.96	43.91	27.33	39.89
...	...	...	...	...	...	...	...	...	...
57	58	6.27	34.64	35.79	0.12	0.95	35.57	0.09	6.62
58	59	1.11	38.84	0.00	2.08	1.54	68.72	0.31	4.83
59	60	0.75	14.11	29.84	0.07	12.15	7.75	0.31	2.30
60	61	2.74	0.00	50.10	0.45	2.06	7.75	0.33	1.38
61	62	8.00	2.43	12.48	2.17	1.09	13.92	0.27	0.00

62 rows × 9 columns

Figure 3 Data load and visualization of available xi variables and Y (total score)
(source: author's work)

The dependent variables taken into consideration are talent, infrastructure, operating environment, research, development, government strategy, and commercial. The output variable (Y) is represented by the total score calculated using all 7 variables. To create the algorithm, and test it, the next step is data preparation.

Step 3. Data preparation – data separation and data split
In this stage, in the workspace, the above dataset is split into two categories: x and Y variables(Figure 4). The next action was to split the data into „ train" and „test" data. Usually, 80% of total inputs are used for training the model and 20% remains for testing (Figure 5)

Data separation on x and y

```
y=df['Total score']
y
```

	Total score
0	100.00
1	62.92
2	40.93
3	40.18
4	39.89
...	
57	5.62
58	4.83
59	2.30
60	1.38
61	0.00

62 rows × 1 columns

dtype: float64

```
x=df.drop('Total score',axis=1)
x
```

	Country codes	Talent	Infrastructure	Operating Environment	Research	Development	Government Strategy	Commercial
0	1	100.00	94.02	64.56	100.00	100.00	77.39	100.00
1	2	16.51	100.00	91.57	71.42	79.97	94.87	44.02
2	3	39.65	71.43	74.65	36.50	25.03	82.62	18.91
3	4	31.28	77.05	93.94	30.67	25.78	100.00	14.88
4	5	35.76	67.58	82.44	32.63	27.96	43.91	27.33
...								
57	58	6.27	34.64	35.79	0.12	0.95	35.57	0.09
58	59	1.11	38.84	0.00	2.08	1.54	58.72	0.31
59	60	0.75	14.11	29.84	0.07	12.15	7.75	0.31
60	61	2.74	0.00	50.10	0.45	2.08	7.75	0.33
61	62	8.00	2.43	12.48	2.17	1.09	13.92	0.27

62 rows × 8 columns

Figure 4 Dara separation for the x variables and Y output
(source: Author's work)

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y, test_size=0.2,random_state=10)
x_train
```

	Country codes	Talent	Infrastructure	Operating Environment	Research	Development	Government Strategy	Commercial
27	28	14.21	70.96	99.56	10.60	9.09	78.14	2.25
21	22	16.97	64.49	76.30	23.56	17.81	72.14	3.08
39	40	7.62	55.44	83.58	15.12	2.21	22.15	0.92
7	8	33.83	81.99	88.05	25.54	30.17	62.35	4.97
44	45	10.56	61.97	56.73	1.49	0.67	60.50	2.95
59	60	0.75	14.11	29.84	0.07	12.15	7.75	0.31
51	52	6.34	55.76	37.61	2.03	0.30	68.86	0.31
10	11	25.43	63.43	61.23	32.63	41.15	82.11	6.72
47	48	8.49	40.74	64.34	9.53	1.02	67.45	0.95
30	31	11.09	64.76	83.25	20.30	14.66	61.43	2.64
32	33	15.87	67.12	70.96	5.96	11.72	70.49	4.30
18	19	28.21	75.19	66.77	27.61	17.81	40.35	4.51
4	5	35.76	67.58	82.44	32.63	27.96	43.91	27.33

Figure 5 Data split into „train" and „test"
(source Autho's compilation)

The coding reflects the instruction given and how the machine splits the dataset in two, making available a subset for training the algorithm and a second subset for testing it.

Step 4. Model building

Looking and inputs and knowing the weights for each input variable, we assume that a linear regression function links the Y and xi. So, first, it was tested the linear regression imported from the sci-kit learn library(see Figure 6).

Scikit-learn is a Python module integrating a wide range of state-of-the-art machine-learning algorithms for medium-scale supervised and unsupervised problems. This package focuses on bringing machine learning to non-specialists using a general-purpose high-level language[10]. It has minimal dependencies and is distributed under the simplified BSD license, encouraging its use in both academic and commercial settings.

Linear Regression

Double-click (or enter) to edit

```
[ ] from sklearn.linear_model import LinearRegression
    from sklearn.metrics import mean_squared_error,r2_score
    lr=LinearRegression()
    lr.fit(x_train,y_train)
    LinearRegression()
```

```
LinearRegression
LinearRegression()
```

Figure 6 Coding for using the linear regression function on a trained dataset.
(Source: Author's work)

Usually, in ML-supervised learning, regression predicts numerical value using a previous dataset. This most basic technique allows to use of algorithms built for continuous data.

The limitation relies on the fact that not all the time the relationship between variables is a linear one and considers the mean of dependent variables.

The linear regression model uses the equation of a line (1) to establish the location of individual points toward the line, and the slope of a line is used to minimize the distance between each data point and the regressional line. So, starting from this it may be trained a linear regression model using data pairs (x, Y).

$$Y = a * x_i + b \qquad (1)$$

Also, to be sure that the estimation is appropriate, it has been employed Random Forest Regressor function to test it on the dataset to compare with linear regression function results. Comparison and evaluation of model performances are compulsory to ensure reliability.

Evaluate the performance of the linear regression.

[10] http://scikit-learn.org

```
y_lr_train_pred
```

```
array([ 2.52001992e+01,  2.68891423e+01,  1.73272293e+01,  3.63517242e+01,
        1.53309627e+01,  2.29701702e+00,  1.16162189e+01,  3.38621008e+01,
        1.43872132e+01,  2.44500911e+01,  2.18561068e+01,  2.98536657e+01,
        3.98917179e+01,  1.14708488e+01,  6.29197314e+01,  3.13603389e+01,
        1.46611301e+01,  2.65997653e+01,  8.49606436e+00,  2.08951627e+01,
        8.87176005e+00,  1.88869615e+01,  3.86660210e+01,  3.08682848e+01,
        3.07331989e+01,  1.54852786e+01,  1.17917629e+01,  2.11754065e+01,
        2.57743261e+01,  3.30351409e+01,  1.52365197e+01,  3.03625816e+01,
        1.37715088e+00,  1.72363565e+01,  1.66640284e+01,  4.83406315e+00,
       -1.15257543e-05,  3.60439079e+01,  6.61651941e+00,  9.71002424e+00,
        1.38482141e+01,  2.48762702e+01,  2.55986209e+01,  2.51889625e+01,
        1.32655581e+01,  9.99998756e+01,  3.05234528e+01,  1.98086394e+01,
        3.44146946e+01])
```

```
[ ] from sklearn.metrics import mean_squared_error,r2_score
    lr_train_mse=mean_squared_error(y_train,y_lr_train_pred)
    lr_train_r2=r2_score(y_train,y_lr_train_pred)
    lr_test_mse=mean_squared_error(y_test,y_lr_test_pred)
    lr_test_r2=r2_score(y_test,y_lr_test_pred)
```

```
[ ] print('LR_MSE (Train):',lr_train_mse)
    print('LR_R2 (Train):',lr_train_r2)
    print('LR_MSE (Test):',lr_test_mse)
    print('LR_R2 (Test):',lr_test_r2)
```

```
LR_MSE (Train): 1.0692552575791068e-05
LR_R2 (Train): 0.9999999590478216
LR_MSE (Test): 1.316408461334044e-05
LR_R2 (Test): 0.9999998350694239
```

```
[ ] lr_results=pd.DataFrame(['Linear Regression',lr_train_mse,lr_train_r2,lr_test_mse,lr_test_r2]).transpose()
    lr_results.columns=['Model','Training MSE','Training R2','Test MSE','Test R2']
    lr_results
```

	Model	Training MSE	Training R2	Test MSE	Test R2
0	Linear Regression	0.000011	1.0	0.000013	1.0

Figure 6 Lines of Python codes used to evaluate the model performance
(source: Authors' work)

Next, to run a comparative experiment, apart from linear regression it was been selected also the RandomForrestRegressor model to be applied and evaluated as performance (Figure 7)

Random Forest

```
from sklearn.ensemble import RandomForestRegressor
rf=RandomForestRegressor(max_depth=2,random_state=5)
rf.fit(x_train,y_train)
```

```
RandomForestRegressor
RandomForestRegressor(max_depth=2, random_state=5)
```

Applying the model to make a prediction

```
[ ] y_rf_train_pred=rf.predict(x_train)
    y_rf_test_pred=rf.predict(x_test)
```

Evaluating the model performance

```
[ ] from sklearn.metrics import mean_squared_error,r2_score
    rf_train_mse=mean_squared_error(y_train,y_rf_train_pred)
    rf_train_r2=r2_score(y_train,y_rf_train_pred)
    rf_test_mse=mean_squared_error(y_test,y_rf_test_pred)
    rf_test_r2=r2_score(y_test,y_rf_test_pred)
```

```
[ ] print('RF_MSE (Train):',rf_train_mse)
    print('RF_R2 (Train):',rf_train_r2)
    print('RF_MSE (Test):',rf_test_mse)
    print('RF_R2 (Test):',rf_test_r2)
```

```
RF_MSE (Train): 19.926711099820132
RF_R2 (Train): 0.92368125175067
RF_MSE (Test): 11.04724333258823
RF_R2 (Test): 0.8615909681039114
```

```
[ ] rf_results=pd.DataFrame(['Random Forest',rf_train_mse,rf_train_r2,rf_test_mse,rf_test_r2]).transpose()
    rf_results.columns=['Model','Training MSE','Training R2','Test MSE','Test R2']
    rf_results
```

	Model	Training MSE	Training R2	Test MSE	Test R2
0	Random Forest	19.926711	0.923681	11.047243	0.861591

Figure 7 Application of RandomForrestRegressor
(Source: Author's work)

Model comparison

A comparison is needed to explain why one model is fitted better than the other one and to explain why the trained algorithm is going to do better in optimization if the right model has been chosen. Figure 8 illustrates how the code lines are written to instruct the machine to compare the results of applying the two models (Linear Regression and Random Forest Regressor)

```
[34] import pandas as pd
     df_models = pd.concat([lr_results, rf_results], axis=0)
     df_models
```

	Model	Training MSE	Training R2	Test MSE	Test R2
0	Linear Regression	0.000011	1.0	0.000013	1.0
0	Random Forest	19.926711	0.923681	11.047243	0.861591

Next steps: Generate code with df_models | View recommended plots | New interactive sheet

```
df_models.reset_index(drop=True)
```

	Model	Training MSE	Training R2	Test MSE	Test R2
0	Linear Regression	0.000011	1.0	0.000013	1.0
1	Random Forest	19.926711	0.923681	11.047243	0.861591

Figure 8 Instructing the machine to perform a comparison.
Source: Author's work

Analysing the comparison results it is obvious that the linear regression function fits better for future predictions using GAII datasets. Looking at findings in both training and testing, the R2 values are 1, and the Mean Squared Error (MSE) values are low therefore one can conclude the errors are insignificant.

Step 6. Data visualization
The experiment findings are more valuable if a data visualization can be performed to better understand how the model fits the initial data and why is useful to repeat the experiment on larger datasets(Figure 9).

```
import matplotlib.pyplot as plt
import numpy as np
plt.figure(figsize=(5,5))
plt.scatter(x=y_train,y=y_lr_train_pred, alpha=0.3)
plt.plot()
plt.ylabel('Predicted AI total score')
plt.xlabel('Actual AI total score')

z=np.polyfit(y_train,y_lr_train_pred,1)
p=np.poly1d(z)
plt.plot(y_train,p(y_train),color='red')
plt.ylabel('Predicted AI total score')
plt.xlabel('Current AI total score')
```

Text(0.5, 0, 'Current AI total score')

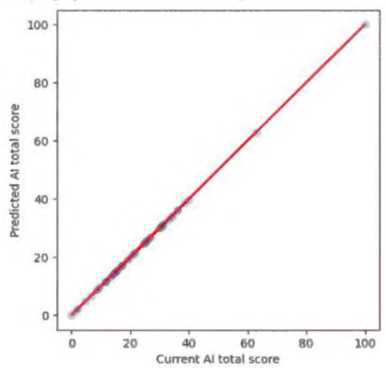


Figure 9 Data visualization using the first run of the ML algorithm
Source: Author's work

Results and discussions

The research reveals the importance of assessing AI adoption and its impact at the firm/country level. Even though there are a limited number of publications on this topic, the approach is consistent and it is grounded on solid methodologies. The paper provides

a comprehensive literature review on the topic and allows readers to understand how the research field evolves.

Using the public dataset of the Global AI Index as input, it was running an experiment of creating an ML algorithm, training and testing it. The paper explains, step by step, the experimental endeavour that benefits from a controlled environment and having access to the collective "wisdom" (scikit-lern.org). Not all the experiments are perfect from the first iteration, that is the case of this experiment too, but it is a good start to explore how the ML algorithm works on a larger dataset.

Conclusions

AI adoption should be seen as a way to generate competitive advantage and raise firm performance. Therefore, measuring the level of AI adoption becomes important not only for comparison reasons but also to identify the main factors with significant impact. In the past recent years, methodologies and measurements were developed to better capture the changes that occurred in the organizational structures and the support offered through country strategies, investments and talent acquisition.

The paper uses the Global AI Index dataset to run an experiment in a supervised machine-learning environment. The use of Python coding helped build an ML algorithm that uses two sets of data: for training and for testing the algorithm. The experiment ran smoothly and the initial assumption that the data are following the linear trend has been confirmed but it should be seen with caution due to the limited number of inputs existing in the initial dataset.

Moreover, the experiment was supported by the Google Colab research environment which allows free access to a controlled experimental environment. The experiment was possible also because building the ML algorithm was supported via the scikit-learn library. However, the experiment is not perfect, nothing comes easy, and there is a need for several iterations and new experiments to improve the algorithm and to be ready to use on large datasets.

Being aware of the limitations, the next step will be to apply the algorithm on a different dataset to demonstrate the performance and the ability to produce intelligible outputs after analysing the initial data.

The experiment should be considered the starting point for new endeavours, exploring how small and medium-sized firms are adopting AI for task efficiency, financial performance or competitive advantage.

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